Stock market index prediction using artificial neural networks trained on foreign markets

AND HOW THEY COMPARE TO A DOMESTIC ARTIFICIAL NEURAL NETWORK

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Abstract

In this report, the location dependency of stock predicting artificial neural networks (ANNs) is investigated. Five ANNs of the type feed forward network are trained on five different stock market indices (Denmark, Germany, Japan, Sweden and USA) and then cross-tested on the other markets to examine what impact this has on the prediction performance. It is found that the ANNs perform similarly, regardless of the market it has been trained on. The conclusion of the study is that ANNs trained on foreign markets perform comparably to a domestically trained ANN. While the results appear to be promising, more research is needed to be able to draw any definitive conclusions.
Sammanfattning

Denna rapport undersöker hur artificiella neuronätverk (ANN) beror på det geografiska läget. Fem ANN av typen feed forward network tränas på fem skilda marknader (Danmark, Tyskland, Japan, Sverige och USA) och testas sedan på samtliga marknaderna för att undersöka vilken effekt detta har på förutsägelsens korrekthet. Rapporten visar att de olika nätverken presterar jämlikt oavsett vilken marknad de tränats på. Slutsatsen för rapporten är att ANN som tränats på utländska marknader presterar jämförd med inhemskt tränade ANN. Samtidigt som resultaten är lovande behövs det mer forskning för att kunna dra slutgiltiga slutsatser.
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Chapter 1

Introduction

Predicting a time series is the concept of predicting $s_{t+1}$ given a set of samples $\{s_0, s_1, s_2, ..., s_t\}$. A considerable amount of research has been conducted in this field as there is a huge amount of applications to this. Examples of applications includes rain rate prediction [12], population growth [13], etc.

One kind of time series is the price of a stock - for each timestamp there is a price of a share. Stock price prediction is considered impossible according to the random-walk hypothesis, which states the stock market prices moves just like a random walk [1]. Despite this, many think that stock prices are predictable to some degree. Although it might be an infeasible task for a human, a computer might have the power to deliver a somewhat accurate forecast. Algorithmic trading is currently in the range of 50 to 60 % of all stocks traded in the US and EU [2]. Some sources says that the number might even be as high as 85 % [3].

Trading using artificial neural networks (ANNs) is a strategy that is showing promising results [9, 5, 7]. It appears as if ANNs are capable of predicting stocks in many different kinds of markets, even in the Chinese market, which is considered a new and volatile market [7].

As an ANN is trained on a specific dataset, the performance is greatly dependent on what data is supplied. This raises a lot of questions regarding the requirements of the dataset. Is it required that the ANN learns from the same market it will predict or does the core mechanisms of a stock market make it possible to transfer learning between regions?

1.1 Problem statement

Does the shared core mechanism enable predictions of a stock market index using an ANN trained with data from a geographically different stock market?

If it is possible to transfer the learning of an ANN to another region, this means that the supplied dataset is not limited to data from the market to be predicted and the range of possible data to be used would be greatly increased. For example, if it is
problematic to find data from a specific market, data could be collected from another market instead.

1.2 Scope

This research was limited to see how the location of the stock market affected algorithmic trading with ANNs. Additionally this research is limited to a time period of 100 work days and five indices will be investigated. These indices are DAX (Germany), Nikkei (Japan), OMX 30 Copenhagen (Denmark), OMX 30 Stockholm (Sweden), and S&P 500 (USA).

1.3 Overview

In Chapter 2 the background of the subject is looked into. The intention is to give the reader a basic understanding of how the stock market works and how the stock price is determined to fully understand why it is so hard to predict. Furthermore it gives the reader an idea of what has been done in the field of stock predicting using ANNs. In Chapter 3 the methods of the experiments are declared. Five ANNs are trained on one market each and then tested on the other markets. Chapter 4 displays the results obtained in the experiments together with a summary. The discussion in Chapter 5 analyses the results to answer the problem statement defined in this chapter. Finally, a conclusion is made in Chapter 6.
Chapter 2

Background

2.1 The stock market

When predicting the future of stock prices using automated algorithms, investors have historically been limited to statistical approaches (moving average, relative strength index, etc). While these indicators might give a hint of what the future looks like, they have proven not to be reliable enough for stock forecasting [6].

A stock market is like any market in the sense that an asset (a share) is offered at a price decided by supply and demand. When a company is listed, the shares of the company is offered at a certain price. After that, traders can purchase shares from others or sell their own shares. A buy or sell order with a certain price that the trader is willing to accept is entered into the system. When a matching order of the opposite kind is found, a trade is executed and the agreed cost of each share is now the stock price. The most common way of prioritising orders are by time. This means that it is important to put the orders as early as possible as it might be too late to sell it at a certain price if a lot of other stockholders wants to sell as well. A less common method is to prioritise large orders over small.

As a stock price might fluctuate greatly over a day, oscillating is a reoccurring problem in algorithmic trading. If the algorithm is programmed to generate a buy signal at the price of 100.00 SEK and the stock price is oscillating around 100.00 SEK, the trader might end up with a lot of transaction fees (courtage) with a small return (if any at all). Different approaches to this includes stopping generating signals for $D$ days after a trade execution or introduce a small band (of $p\%$) around the target price where the algorithm will not generate signals after the trade [10].

The number of trades in a day for a specific stock is called the trading volume. It is important to note that it is the traders themselves who affect the price of the stock. If a scandal is brought to surface in a company, the stock price could stay the same if no one decided to sell. However, as it could be hundreds of thousands different shareholders, this is not likely to happen. Instead, traders owning this stock will try to sell their shares at a certain price. If this price does not match what buyers are willing to pay, the owner has to place a new sell order at a lower price and thus, the price of the stock
is falling. The displayed stock price is determined by the latest successful transaction. A high trading volume means that the market is liquid, a lot of money is in movement, which is usually a sign that the investors are insecure about the future of the stock \[11\].

A stock has three main components determining its fluctuation. There is the long-term trend which is the most interesting to long-term investors as it measures how the stock is doing over time. The second component is the seasonal trend. This trend is affected by seasons. For example, an ice cream company stock is likely to rise in the summer and fall in the winter. At last, there is the day trend, how a stock price varies during the day. The day trend is what day-traders are dealing with when trying to find the right stocks for their portfolio and it is likely the one hardest to predict. It involves sudden breakthroughs (like the presentation of a new product) which are very hard to predict.

The problem with statistical approaches is that they are not considering these different trends. A moving average with the parameters \((200, 1)\) is not likely to predict that summer is coming and the ice cream stock is likely to rise. Humans are more suited to find these kinds of patterns compared to automated methods, but this might change, as ANNs are getting more powerful.

### 2.2 Artificial neural networks and time series prediction

#### 2.2.1 Artificial neural networks

An ANN consists of three disjoint sets of nodes; input, hidden (also known as middle) and output neurons, see Figure 2.1. These sets are connected by weighted and directed edges. The edges depend on the complexity of the network. In the most simple cases of ANNs, the edges are limited to being forward edges.

If the goal is to predict the closing price of a stock tomorrow, the input set could be \{Open\(_t\), High\(_t\), Low\(_t\), Close\(_t\)\} from the day before and the output neuron would simply be \{Close\(_{t+1}\)\}.

The input will be mapped to an output in some way by the hidden neurons. A dataset, for which the desired output is known, is provided to configure the network. For the first iteration, all weights are randomized and then, for each iteration, an error is calculated:

$$
\vec{e} = \vec{z} - \vec{d}
$$

Where \(e\) is the error, \(z\) is the achieved value and \(d\) is the desired value.

An algorithm is used to alter the weights (starting with the strongest weight as it affects the result the most) of the connections to give a result closer to the desired output. An example would be the Levenberg-Marquardt backpropagation algorithm:

$$
S(\beta) = \sum_{i=1}^{m} [y_{i} - f(x_{i}, \beta)]^2
$$

\[1\] Long-term average from 200 days compared to the short-time average from 1 day
Figure 2.1: An example of a simple ANN with the input set $i_j \in I$, hidden set $h_k \in H$ and output set $o_n \in O$ and all edges has a weight $w_m$.

where $m$ are the timestamps for which there are $(x_i, y_i), i \in m$. The goal is to minimize the sum $S(\beta)$. For stock forecasting this means that one could provide the ANN with a dataset made up by the history of the stock. For every day, it is known what the “desired output” is, as it is possible to look at the next day (or even on a minute-to-minute basis) and see what the price was and modify the ANN so that it will be closer to this.

2.2.2 Stock predicting using neural networks

There are three types of analysis methods used to predict stock prices. These are the technical analysis, the fundamental analysis and the quantitative analysis.

The technical analysis is the “computer friendly” type of analysis as it revolves around numbers. The analysis relies on the theory that one can predict the stock price by looking at the price and volume history. Statistical readings, as the moving average, are used to make the decisions of buying or selling.

Fundamental analysis relies on the market efficiency theory being wrong. The market efficiency theory states that everything known about a company is reflected in the stock price – the price is effective [4]. Rejecting this theory, the fundamental analysis theory
states that there are under- and overvalued stocks. If a stock is undervalued it means that the price of the stock does not reflect the value of the company.

Quantitative analysis treats stocks as random variables and uses mathematical and statistical analysis to describe how this random variable will function. This kind of analysis works even if the random walk-hypothesis is correct, in the same way as one cannot predict what a dice will show but can still analyse the likelihood of different outcomes.

The current focus in algorithmic trading is machine learning and ANNs. They both revolve around computers learning how the stock market behaves. Both of these are relatively new fields of study but initial research has proven to be promising.

Research done by Qing Cao et al [7] shows that using ANNs for stock predicting is very auspicious. The ANNs in Qing Cao’s experiments were tested on the Chinese stock market. Three different kinds of ANNs were tested (as referred to by Qing Cao as the univariate ANN model, the CAPM ANN model and the three-factor ANN model). These ANNs were based on linear models and they all perform better than their linear counterpart in terms of mean absolute deviation (MAD), mean absolute percentage error (MAPE), and mean square error (MSE). Their dataset covered a time period from January 1, 1999 to December 31, 2008 and 367 public corporations. The predictive power of neural networks proves to be superior to the predictor variables Beta, CAP and B/M according to Qing Cao et al. Even on an emerging market with high volatility, like the Chinese market, the neural network managed to out-perform more classical methods. It was also found that adding relevant variables to the models improved the predictive power [7].

Refenes et al [9] tested a neural network to perform a stock prediction on the London stock market and compared it to classical statistical techniques. The ANN was trained on 143 stocks for six months and then evaluated for another six months. This cycle was repeated during a longer time period (May 1985 to December 1991). Running time for this training was about 3 - 4, days but it is worth noticing that the paper was written in 1994. Furthermore, Refenes et al [9] also draws the conclusion that the amount of hidden layers and neurons are not a deciding factor. The Root Mean Square (RMS) error remained stable on a low level (fluctuating between 0.044 to 0.072) for different values. The result of the testing is though the difference is not huge, a two-layered network is preferred. The complexity of the network will affect the amount of iterations needed for a stable RMS error [9]. The paper indicated that the neural network technique outperforms classical statistical approaches [9].

Molin and Suljkic compared the predictability of different markets (Stockholm, Barcelona, and Korea) using ANNs. They received different results for different markets, with the Stockholm market appearing to be more predictable than the Spanish and Korean counterparts. The Autoregressive-Moving-Average (ARMAX) method, which is not an ANN but was used as comparison, was off by up to 200-500% from the real value while the Adaptive Neuro Fuzzy Inference System (ANFIS) ANN had an error rate of a few percent. According to Molin and Suljkic, this was due to how the ARMAX method is based on a linear prediction function [8].
Instead of the mentioned methods, Reid et al proposes an alternative way of predicting time series, called Polychronous Spiking Neural Networks (PSN). The idea of PSNs is put forward as an alternative to the more classic ANNs which are too susceptible to price fluctuations [5]. While Reid et al are not the first to suggest PSNs for financial predicting purposes, not much research has been done in the past to explore this. Most implementations of PSNs are actually subsets of more traditional machines [4].

To our knowledge, no research has been done on how an ANN, which learned from a market in one region, will perform in another region of the world.
Chapter 3

Methods

3.1 Data

As a representation of each market, a stock market index was used. The index can be seen as an average value of the most impactful stocks on a certain market. This is a weighted average so that a large company (like Hennes & Mauritz in Sweden) will have a larger impact on the value of the index. We consider the index to be a good representation of the stock behaviour in a country.

The indices used in the experiment were chosen based on location (see Table 3.1). Sweden, Denmark and Germany are close to each other geographically. If the region of the market has an impact on how it behaves, these countries are expected to behave similarly while the Japanese and American counterparts would differentiate.

When it comes to indices used (as there exists several on each market), the largest indices with companies in a wide range of fields were chosen. One thing to consider is that Nikkei and S&P 500 are made out of significantly more companies (225 and 500 respectively compared to the 30 of DAX, OMX 30 Stockholm and OMX 30 Copenhagen).

Table 3.1: Indices used in the experiment and their region

<table>
<thead>
<tr>
<th>Nation</th>
<th>Index used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Denmark</td>
<td>OMX30 Copenhagen</td>
</tr>
<tr>
<td>Germany</td>
<td>DAX</td>
</tr>
<tr>
<td>Japan</td>
<td>Nikkei</td>
</tr>
<tr>
<td>Sweden</td>
<td>OMX30 Stockholm</td>
</tr>
<tr>
<td>USA</td>
<td>S&amp;P500</td>
</tr>
</tbody>
</table>

For each market in Table 3.1 an ANN was trained over a time period from 2014-01-01 to 2014-06-01, using historical stock data from Yahoo Finance (http://finance.yahoo.com/). Five months of data was used for training as research shows that after a certain time period, old data becomes obsolete in its impact on the future stock prices [9]. After the training completed, the ANNs were tested and evaluated on all five markets between 2014-06-02 and 2014-12-01.
3.2 Artificial neural networks

A feedforward neural network was created using the `fitnet(10)` method of Matlab, see Figure 3.1. The feedforward network was used as Qing Cao states that it has been shown that these kinds of networks approximates continuous functions well. Ten hidden neurons were used as configuration with a higher amount of neurons did not seem to improve the results when tested which corresponds to Refenes report where it was stated that the amount of hidden neurons was not a deciding factor.

After an ANN had been trained on a specific index, it was tested and evaluated on the market of the index along with the other markets. This would be the most logical approach as if any market behaved in a peculiar way, this could be observed in the results.

The inputs of the networks were, for a day $t$, the daily high, low, opening, and closing price. This resulted in a prediction of the closing price on day $t+1$. These parameters were chosen as it is what is saved as historical data for a stock. Research indicates that more variables can result in improved predictive power so we wanted to use as many as possible.

$$\begin{bmatrix} \text{high}_t \\
\text{low}_t \\
\text{open}_t \\
\text{close}_t \end{bmatrix} \Rightarrow [\text{close}_{t+1}]$$

(3.1)

This means that our predictions are short-term predictions. Every day, the ANN predict the closing price of the next day. For the next prediction, the ANN gets the correct values to do the next prediction. This means that older predictions are not used in future predictions.

As the markets might differ in terms of currency and index representation (how many companies are represented, what the value of these companies are, etc.) all data was normalized for each market. The data was normalized using the following equation

$$p_{norm} = \frac{p - \min(P)}{\max(P) - \min(P)}$$

(3.2)
where $P$ is the complete time series. The different time series (daily high, low, closing and opening price) were normalized individually for each market.

3.3 Evaluation

To evaluate the overall prediction performance of an ANN on a specific market, an error sum was calculated. The error sum is using the absolute value of each error. This is to prevent that large error instances of opposite sides cancels each other (An error $e_1 = 5$ could potentially cancel out an error $e_2 = -5$ if using the normal sum).

Additionally, a performance rating, $p$, was calculated for each ANN and each test. This performance rating is simply how the ANN performed compared to the domestic ANN in terms of error sum.

$$p = \frac{\sum_{0}^{T} e_m(t)}{\sum_{0}^{T} e_d(t)}$$

(3.3)

where $e_m(t)$ is the error of the foreign ANN and $e_d(t)$ the error of the domestic ANN at the time $t$. $T$ is the amount of days. In our experiments $T = 100$. 


Chapter 4

Results

Since each training session of an ANN results in a unique ANN, we trained 100 networks on every market to be evaluated. That is, we had 100 ANNs trained on the German index and they were all tested on all markets (including the German). This was done for all markets. The graphs represented are the average of all these predictions. This was done to limit the impact of coincidence.

As can be seen in the graphs (see Figure 4.1, 4.2, 4.3, 4.4, and 4.5), the predictions of foreign ANNs were comparable to the ones of the domestic counterpart. The biggest difference in error sum was the ANN trained on Nikkei and then tested on OMX 30 Copenhagen (see Table 4.1) with a performance of 1.0113 (see Table 4.2). This means that the worst ANN performed 1.13 % worse compared to the domestic ANN. In eight cases, the foreign ANN performed better than the domestic but only by a small amount. The ANN trained on the German index and tested on the Japanese index was the one performing best, performing 1.46 % better than the domestic ANN.

The purpose of this research is not to evaluate the predictive performance of ANNs, but rather to evaluate how much better a domestic ANN is, compared to one trained on a foreign market. However, our results indicates that the ANNs have an easier time predicting the DAX and Nikkei indices (indicated by the lower error sum in Table 4.1) while the OMX 30 Stockholm and S&P 500 proves to be harder.

Table 4.1: Error Sum. The sum of all the absolute errors in the predictions.

<table>
<thead>
<tr>
<th>ANN trained on</th>
<th>DAX</th>
<th>Nikkei</th>
<th>OMX 30 Sto.</th>
<th>OMX 30 Cop.</th>
<th>S&amp;P500</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nikkei</td>
<td>4.7765</td>
<td>4.8161</td>
<td>5.9649</td>
<td>5.2519</td>
<td>6.1450</td>
</tr>
<tr>
<td>OMX 30 Copenhagen</td>
<td>4.7413</td>
<td>4.8507</td>
<td>5.9687</td>
<td>5.1930</td>
<td>6.1738</td>
</tr>
</tbody>
</table>
Table 4.2: Performance rating table. The error sum of an ANN compared to the domestic ANN. A value below 1.0 means that the ANN performed better than the domestic ANN.

<table>
<thead>
<tr>
<th>ANN trained on</th>
<th>DAX</th>
<th>Nikkei</th>
<th>OMX 30 Sto.</th>
<th>OMX 30 Cop.</th>
<th>S&amp;P500</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAX</td>
<td>1.0000</td>
<td>0.9854</td>
<td>1.0040</td>
<td>1.0011</td>
<td>1.0095</td>
</tr>
<tr>
<td>Nikkei</td>
<td>1.0004</td>
<td>1.0000</td>
<td>0.9971</td>
<td>1.0113</td>
<td>0.9911</td>
</tr>
<tr>
<td>OMX 30 Stockholm</td>
<td>1.0071</td>
<td>1.0093</td>
<td>1.0000</td>
<td>1.0006</td>
<td>0.9976</td>
</tr>
<tr>
<td>OMX 30 Copenhagen</td>
<td>0.9930</td>
<td>1.0072</td>
<td>0.9996</td>
<td>1.0000</td>
<td>0.9958</td>
</tr>
<tr>
<td>S&amp;P500</td>
<td>1.0021</td>
<td>0.9917</td>
<td>1.0039</td>
<td>1.0038</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

4.1 Summary

In all cases, the foreign ANNs performed at a level comparable to the domestic ANN. In eight out of twenty cases did the foreign ANN perform better compared to the domestically trained ANN. The ANN trained on the German DAX index and tested on the Japanese Nikkei index performed best compared to the domestic counterpart (1.46 % better than the Japanese ANN) while the ANN trained on Nikkei and tested on the Danish OMX 30 Copenhagen performed worst (1.13 % worse than the Danish ANN).
Figure 4.1: ANN trained on the German index DAX. Red is the prediction and blue is the actual value.
Figure 4.2: ANN trained on the Japanese index Nikkei. Red is the prediction and blue is the actual value.
Figure 4.3: ANN trained on the Danish index OMX 30 Copenhagen. Red is the prediction and blue is the actual value.
Figure 4.4: ANN trained on the Swedish index OMX 30 Stockholm. Red is the prediction and blue is the actual value.
Figure 4.5: ANN trained on the American index S&P 500. Red is the prediction and blue is the actual value.
Chapter 5

Discussion

It is important to note that we do not make any claims on the predictive powers of ANNs. Instead, we investigated whether it matters what market the ANN was trained on. Our results strongly indicate that it does, in fact, not matter. All across the results, domestic and foreign ANNs perform comparably. The difference is seldom higher than 1.0 % (see Table 4.2) between the domestic and the foreign ANN.

The results presented in this report are very promising as it indicates that larger datasets could be used for the training phase without negatively affecting the performance. This means that if a new emerging market with a lack of historical data is to be predicted, an ANN trained on another market is likely to do stock forecasting as good as an ANN trained on this specific market would have.

We believe that a big reason to why the ANNs perform similarly is that our research is done on the index of each market. The index is the weighted average of the biggest companies in the country and these companies are likely to be present on the international market. They are thus expected to be affected by the same kind of news, laws and international events. The results might be different if indices with only local companies were used.

It is worth to have in mind that analysing stock predictions is different from other time series predictions. For example, consider a stock currently traded at the price of 100.00 SEK. The ANN predicts that in a week, it will be worth 113.00 SEK. We buy the stock and sell it one week later at the actual value of 103.00 SEK. The return of investment is +3.00 SEK but the actual prediction was not very good, it was off by 10.00 SEK. It forces us to ask: What does good performance really mean? In our experiments, we have judged the performance of an ANN $A_i$ on a market $M_k$, $i \neq k$ by comparing it to the performance of the ANN $A_k$ trained on $M_k$. This means that a bad performance in our experiments does not necessarily mean that the ANN would be of no use for a stock trader looking to make money as an overshooting prediction from the ANN (and thus, triggering a buy signal) might generate a return of investment — even if it is not as much as predicted by the ANN. It means that an ANN trained on another market performs similarly to the ANN trained on that specific market.

It is worth remembering that the indications our results shows are limited to the
type of ANNs we have tested. As feed forward networks are relatively simple versions of ANNs it might be that more complex versions have a higher sensitivity to what data it is trained on.

5.1 Improvements

The best way to improve this research would to extend the scope. In a more extensive research, different types of ANNs could be tested (for example a Nonlinear Autoregressive Neural Network) to see if the impact of the market location is dependent on what kind of ANN one is using.

For more extensive research, this experiment could be repeated over different time periods and different indexes. It might be the case that these results only specifically reflect this time period and that it depends on what state the world currently is in. Furthermore, one could limit the scope to regional companies only to investigate if local Swedish company stocks behave in the same way as local American stocks for example.

Additionally, different types of markets could be used. For example, it could be investigated whether the stocks of companies in the oil industry are displaying similar characteristics. This could result in a more refined and specialized ANN compared to an ANN who trained on a national index where a lot of different industries are represented.

To really be able to say anything about the predictive performance of our ANNs we would have to compare it to some other stock predicting techniques tested on the same time period. We can examine the error sum table (Table 4.1) and say that $e = 6.0053$ is a small number, but as we are dealing with normalized data and have nothing to compare this to, it really does not tell us anything about the predictive powers of the ANNs. It is rare that a stock market index would fall or rise with more than 2 % in a day so even a strategy that randomly predicts a value $p$ where $0.98v \leq p \leq 1.02v$ (where $v$ is the value of the day before) could achieve a low error sum.

Questions should be raised about our choice of evaluation. We picked the error sum to evaluate the relative performance of the ANNs. Consider a scenario where an ANN gets a prediction completely wrong on one day but then proceeds to predict all the following days perfectly. In this hypothetical scenario, the error sum would be pretty large due to the initial prediction, while the predictive power of the ANN is impressive. We can see in our results that this was not the case but it shows that evaluating with an error sum could be misleading.

Another scenario where an error sum would be deceiving would be if one ANN always overshoots by 2 % while the other undershoots by 2 %, this would lead to a similar error sum, but could you really say that these ANNs perform comparably on this market? Once again, we can see in the error graphs of our results that this is not the case either. In all cases, we see how the error graph of a domestic ANN is very similar to that of a foreign ANN. However, it would be preferable to have this reflected in the evaluation.
5.2 Future research and implications

It is clear that our research shows some promising results but that more research would have to be conducted before we can safely say that it is worth it to expand the scope of the dataset used for training. One would probably need to investigate what markets are susceptible for this kind of dataset expanding. It might be that our results are limited to our scope of national indices and not be useful for specific stocks.

This research indicates that an ANN could be trained on multiple indexes without a performance loss. Previous research in the field of stock predicting ANNs has often assumed that only the time series of the financial asset should be used for training but our research indicates that one could benefit from using a larger dataset, using other indices as well. If the assumption that the performance of an ANN increases with the size of the dataset holds true, this means that better predictions could be achieved.

To further extend the viability of our results, different time scales could be tested. We tested a six months period — other time periods might show different results.

Groundbreaking research in the field of stock forecasting with ANNs is not likely to be done with simple feed forward networks as the one we have tested. Therefore, our results might only be seen as an encouragement to explore this concept in more complex networks.
Chapter 6

Conclusion

After conducting these experiments, we can conclude that the results strongly suggest that an ANN can perform comparably on a market different from the one it was trained on. The implication of this is that when stock predicting using ANNs, it is definitely worth to explore expanding the dataset with data from other markets. We can not conclude that this holds true for all time series sharing the same core mechanisms as our research was limited to stock predicting.
Bibliography


